INTERNATIONAL JOURNAL OF TECHNOLOGICAL EXPLORATION AND LEARNING (IJTEL)
www.ijtel.org

Fisher Algorithm: Variations And Applications

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Abstract—**This paper examines Fisherface (Linear Discriminant Analysis) methods, its different modifications as applied to feature extraction in face recognition. Researchers showed that Fisher algorithm, though it performs better than PCA, Eigenface and some other fundamental methods, computational complexity, enormous hardware resources usage are inhibitors to its implementation. Different versions or adaptations of Fisher algorithm had been developed, and applied to face recognition and validated using some of the available public face databases. If fisher algorithm and its various variations had so marvelously helped in face recognition, application of this effective dimensionality reduction method can be applied to research area of iris recognition system. This will in return enhance performance of biometric systems in its application to computer security and surveillance.**

Keywords: Databases, Face Recognition, Fisher's Linear Discriminant Analysis, Recognition Accuracy.

I. INTRODUCTION

Recently, face recognition is attracting much attention in the society of network multimedia information access [1] (Shang-Hung, 2000). For the generic framework for face recognition and its variations, reader can consult [1] (Shang-Hung, 2000;). Face recognition is largely motivated by the need for surveillance and security, telecommunication and digital libraries, human-computer intelligent interaction, and smart environments [2; 3; 4; 5].

This paper examines the generic fisher linear discriminant analysis, its various available versions, their efficiency (recognition accuracies) and face image databases on which they were tested.

Fisherface Algorithm

The Fisherface algorithm is as shown below:Let $\square_i$ and Σ_i be the mean vector and covariance matrix for class i.

Define

$$S_b = \sum_{i=1}^{c} n_i(\square_i - \square)(\square_i - \square)^T \qquad (1)$$

$$= \sum_{i=1}^{c} n_i(\mu_i \mu^T)$$

And

$$S_w = \sum_{i=1}^{c} \sum_{Z_k \in i}^{.} (Z_k - \mu_i)(Z_k - \mu_i)^T \qquad (2)$$

Note that in the Z-scale, μ=0. We can always assume that S_wis non-singular else the Principal Component Analysis (PCA) is used to reduce its rank so that the resulting reduced dimensional subspace has non-singular Sw.

Belhumeur and his research group developed an algorithm called Fisherface to determine a matrix Γ=(γ_1,γ_2,. .,γ_q) that maximizes the ratio of the between class scatter to within class scatter given by:

(γ^T S_B γ)/(γ^Tγ_w γ) (3)

under the constraint

$$\Gamma^T S_w \Gamma = I \qquad (4)$$

when c=2, this technique is called Fisher's linear discriminant analysis (LDA) [6].

When c> 2, it is traditionally called canonical covariate analysis [7].

The Fisherface method is a well-known technique in classification and discriminant analysis. The optimal

situation,from pattern classification standpoint, is encountered when the x_i are normally distributed for each class i with each class having the same covariance matrix, i.e

$$\Sigma_i = \Sigma \qquad for\ i = 1,2,..,c$$

when not all $\Sigma_i = \Sigma$, important classification information could be lost,hence the difference among the $\Sigma_i's$ needs to be considered.

While the Fisherface method does not need the assumption of normal class distributions, its absence could result in suboptimal classification [7;8].

II. REVIEW OF LITERATURE

Peter developed a face recognition algorithm which is insensitive to large variation in lighting direction and facial expression. Taking a pattern classification approach. Each pixel in an image was considered as coordinate in a high-dimensional space. The image lied in a 3D linear subspace of the high dimensionality image space. Since faces are not truly lambertian surface, they were linearly projected into a subspace in a manner which discounts regions of the face with large deviation (shadowed) and later projected the image into sub-space based on Fisher's Linear Discriminant. The method was discovered to produce well separated classes in a low-dimensional subspace even under severe variation in lighting and facial expression and performed better than Eigenface technique [9].

Chengjun and Harry developed an enhanced Gabor Fisher Classifier (GFC) for face recognition [10]. The GFC method, which was robust to change in illumination and facial expression applies the enhanced fisher linear discriminant model (EFM) to an augmented Gabor feature vector derived from the Gabor wavelet representation of face images. The classifier can be used for multi-class problem. Comparative studies of different similarity measures applied to various classifiers were performed. The method was compared with existing face recognition algorithms such as Gabor wavelet method, Eigenfaces, Fisherfaces, EFM and some hybridized methods. It was discovered that its performance was much better with 100% recognition accuracy. (Shiguang*et al*., 2002) employed extended fisherface for face recognition [11]. From one example image per person, extended fisherface generated many images through which the fisherface was trained. This was done to overcome the problem of inability to apply fisherface where single image is available for training. The method was discovered to outperform Eigenface and template matching methods.

In 2003, Jian and his colleagues developed for face feature extraction and recognition. In the framework, Principal Component Analysis (PCA) and Kernel-PCA (KPCA) are first used for features extraction. The resulting PCA based linear features and KPCA based non-linear features were integrated by complex vectors and complex LDA was further employed for features fusion. The proposed method was tested on a subset of FERET database [12].The result of the experiment reveals that Complex Fisherfaces outperforms Fisherface and Kernel Fisherfaces. In the same year, Florent introduced a novel deformable model for face mapping. The goal was to model transformations between face images of the same person as a global face transformation may be too complex to be modeled in its entirety. Mahalanobis metrics which consistently outperforms other distances was employed to validate the system and recognition accuracy of the developed system was 96.0% compare to the best recognition accuracy of Fisherface which is 93.2% [13]. Yangrongand his group developed Sliced Inverse Regression (SIR) face which is insensitive to lighting variation and facial expression. used a novel data dimension reduction method proposed in statistics, they developed an appearance based face recognition algorithm which is insensitive to large variation in lighting direction and facial expression [8]. It was able to an optimal reduced subspace (with the fewest dimensions) resulting in a lower error rate and reduced computational expense. Tested on Yale face database, and using the same simple nearest-neighbor classifier on the images, Sirface performed better than Fisherface in subspace reduction. Sirface was able to perform 90% recognition accuracy against 78.6% in the case of fisherface. Xiaogang and Xiaoou proposed a face difference model that decomposes face difference into three components: intrinsic difference, transformation difference, and noise using the face difference model and a detailed subspace analysis on the three components [14]. A unified framework for LDA, PCA and Bayesian algorithms was developed. They developed a unified framework for subspace analysis using this framework they discover the inherent relationship among different subspace method and their unique contributions to the extraction of discriminating information from the face difference. They also constructed a 3D parameter space that uses the three subspace dimension as axis within this parameter space. The developed unified subspace analysis method achieved better recognition performance than the standard subspace methods on over 2000 face image from the FERRET database.

Ling proposed face recognition (FR) using new Hidden Markov Model (HMM) method to model classes of face images [15]. A set of fisher scores was calculated through partial derivative analysis of the parameters estimated in each HMM. These fisher scores are further combined with traditional features such as log likelihood and appearance based features to form feature vectors that exploit the strengths of both local and holistic features of human face. Linear discriminant analysis (LDA) was then applied to analyze these feature vectors for FR performance improvements. The developed model outperformed stand-alone HMM method and fisher face method which use appearance based feature vectors. They further reveals that by reducing the number of models involved in the training and testing stages of LDA, the proposed features generation scheme was able to maintain very high discriminative power at much lower computational complexity compared to traditional HMM based FR system. Also in the same year, Xiao and his group developed an extended fisherface with 3D morphable model [16]. This was done to overcome the training requirement in implementation of fisherface. To tackle the problem, fisherface method was extended by utilizing 3D morphable model to derive multiple image of a face from one single image. When the system was applied on Olivetti Research Laboratory (ORL) and UMIST face database at rank-1, extended fisherface performs better than Fisherface method with (76.3% and 85.4% on the two databases respectively) and Eigenface method with (72.1% and 73.8% on the two databases respectively). Xiao-Sheng 2005 developed Inverse Fisher Discriminant Analysis for face

recognition [17]. The method combined PCA plus LDA techniques that has two- phrase framework to deal with high dimensional space and singular cases. Inverse fisher criterion was augmented by adding a constraint in PCA procedure so that singularity phenomenon will not occur. At rank-5, when the method (IFFace) was evaluated on ORL, FERET and ORLFERET face databases, IFFace performed well with 92.5% against 87.6% of Fisherface (ORLFERET) [18].

In 2008, Spectra Regression Discriminant Analysis (SRDA) was developed to overcome time and hardware resources consumption complexities of the conventional Linear Discriminant Analysis (LDA) as a method of features extraction and preservation of class separability in images [19]. Through the use of spectral analysis, SRDA was able to cast discriminant analysis into a regression framework that facilitated both efficient computation and the use of regularization techniques. There was no eigenvector computation which greatly saves both computation time and computer memory used in the computation. It was developed from LDA but has great computational advantage over LDA. The approach combines spectral graph analysis and regression to provide an efficient and effective approach for discriminant analysis.

Cheng and his group (2010) proposed a Local Fisher Discriminant Embedding (LFDE) method where face images are mapped into face subspace for analysis. This is different from LDA, which effectively sees only the Euclidean structure of face space. It finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure [20]. The method was compared with PCA, LDA, Locality Preserving Projections (LPP), and Unsupervised Discriminant Projection (UDP). LPP was developed by He and his colleagues [21; 22] and UDP was developed by Yang *et al.*, for face recognition [23; 24; 25]. The system was tested on PIE, FERET and ORL face databases. On PIE database, maximum recognition rate of each of the methods is as follows: PCA: 38.14%, LDA: 46.74%, LPP: 53.61%, UDP: 58.76% and L-Fisherfaces: 80.76%. L-Fisherface has highest outstanding recognition in FERET database and on ORL, the recognition of the method was the highest with 96.3% recognition accuracy [26].

Summary of literatures reviewed is showed in table 1.Majority of applications of fisher algorithm examined dealt with face recognition system.

III. CONCLUSION AND RECOMMENDATION

Fisherface, one of the most effective face recognition methods was scrutinized. Application of its dimensionality reduction prowess is highly coveted in iris recognition system. Iris, as a biometric characteristic in man is more permanent than every other biological traits[27; 28]. In this age, when there is a great need for robust biometric personal recognition system because of increase in crime rate globally [29]. Employment of proven method(s) will hasten the rate of actualization of desired system, which will enhance both inter and intra-boarder movement of people.

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TABLE I. SUMMARY OF DIFFERENT FISHER ALGORITHMS AND THEIR AUTHORS

Year	**Authors**	**Version/Method**	**Motivation**	**Advantage/Efficiently**	**Database**
1997	Peter *et al*	The image was projected into a Fisher Linear Discriminant's sub-space.	To get a better recognition rate under varying illumination but fixed pose.	Fisherface method has error rates lowered by 4.6% than the Eigenface method has error rates of 47% and required less computation time	Harvard & Yale Database
2000	Shang. Hung Lin	Generic framework method. recognizer and the face detector follow the same framework. They both have a feature extractor that transforms the pixel of the facial image into a useful vector representation.	Is to show the readers the generic framework for the face recognition system and the variants that are frequently encountered be face recognizer.	Face recognition approach possesses one great advantage which is its user-friendliness.	Indexing and retrieving Database
2002	Chengjun and Harny	Enhanced fisher linear discriminant model method.	To feasibility a new GFC method that has been successfully tested on face recognition using a data set.	The novel GFC method achieves 100% accuracy face recognition using only 62 features. It performed excellent well compared to some conventional methods.	FERET Database
2002	Shiguang et al	Fisherface is one of the most successful approaches compared with Eigenface which extracts most expressive features.	To derive a multiple image of a face from one single image	Extended fisherface face for face recognition performance improve compared with the conventional Eigenface and matching techiques.	Bern face Database
2003	Jian*et al*	The mean recognition rate of complex fisherface is over 2% higher than those of fisherface and kernel fisherface .automate method.	To make complex fisherface more powerful than fisherface kernel fisherface.	The LDA(or KFD) is really helpful for improving the performance of PCD (or KPCD) for face recognition.	FERET Database
2003	Florent *et al*	A novel deformable model for face mapping	To reduce the computational load and for a fair comparison with fisherface	The advantage is to model the transformation between face images of the same person.	FERET Database (subset). 96% recognition compared with

					93.2% of fisherfaces.
2003	Yangrong et al	Sirface is more efficient than fisherface in terms of both error rate and computational expense.	To reduce in the context of appearance-based face recognition by using Sirface technique.	Sirface has a associate formal hypothesis testing procedure for determining the optimum dimensionality.	Yale face database
2003	Xiaogang et al	The unified subspace analysis method achieves 100% accuracy using only a small number of features.	To analysis method that achieves better recognition performance than the standard subspace method	A unified subspace analysis method based on a new framework for the three subspace face recognition method; PCA, LDA and Bayesian algorithm.	FERET Database
2005	Ling et al		To develop a new feature vector generation scheme based on multi- class mapping of fisherscores.	The effectiveness of the proposed feature vector generation scheme is testified by higher RR and lower computational complexity	Georgia Tech face Database (GTFD)
2005	Xia et al	Recognition rate of fisherface method is 85.4% while that of Eigen face method is 73.8%	To make impressive performance improvement compared with conventional eigenface method	The effectiveness of fisherface is extended for face recognition 3D Morphable model is utilized to deriive multiple image from a single example image to form the set for fisherface	ORL Database & UMIST Database
2005	Xiao et al	The average recognition rates are 92.5% for IFface , while for fisher face it is only 87.6%	To proposed a new fisher discriminant analysis framework PCA plus LDA method	The effectiveness of new IF face method is to compare the performance between fisher face and IF face	ORL and FERET database
2006	Itaitao et al	This implies that the existing eigenface and fisherface based algorithm/system can be scaled up easily by sing the proposed SVC/PCA	Propose a new IPCA method based on the idea of a singular value decomposition (SVD) updating algorithm	SVDU-IPCA algorithm can be used in both method with a very small degradation in recognition accuracy	FERET, AR and Yale B, database
2008	Ben Niu et al	To show the relationship between the accuracy rate of the three algorithm and the dimension of th feature vectors used for recognition.	propose a two-dimensional (2D) laplacianfaces method for face recognition.	It can maximally preserve the locality of the geometric structure of the sample space to extract the most salient feature for classification.	FERET and AR Database

			which are locality preserved embedding and image based projection.		
2008	Deng Caiet *al*	Linear Discriminant Analysis (LDA) has been a popular method for extracting feature that preserves class separability.	Propose a novel algorithm for discriminant analysis called spectral Regression Discriminant Analysis (SRDA).	LD has been widely used in many fields of information processing, such as machine learning, data mining and information retrieval.	(CMU) PIE Database
2009	Xuebin *et al*	An efficient method for human face recognition using nonsubsampledcontourlet transform and support vector machine can make the best recognition rates increase by 2.85% for YaleB database and 1.87% for ORL database,	Proposed has performs better than the wavelet-based method. Compared with the wavelet-based method,	To improve the recognition rate in different conditions, a multiscale face recognition method based on nonsubsampledcontourlet transform and support vector machine	Yale and ORL Database.
	Tomoa kiet *al*	This method improved memory usage, computational cost, and data size about the feature per person. In addition, the recognition improvement reaches up to 46.9% when compared with the GEC method	proposed a face recognition system using pseudo Fisherface for an embedded application	the recognition rate of various illuminated *fc* probe set is better than the best FERET rate to use original generic dataset which includes various illuminated images.	FERET database.
2010	CHEN G *et al*	By using Local Fisher Discriminant Embedding (LFDE), the face images are mapped into a face subspace for analysis	the proposed L-Fisherfaces provides a better representation and achieves higher accuracy in face recognition.	LFDE finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure. Different from Locality Preserving Projections (LPP) and Unsupervised Discriminant projections (UDP), which ignore the class label information	PIE, FERET, and ORL face databases